What Can We Learn From a Year-Long, Live Streamflow Forecasting Competition?

HydroML
Penn State University
May 18, 2022

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UPSTREAM TECH

Smart climate solutions
for a changing planet

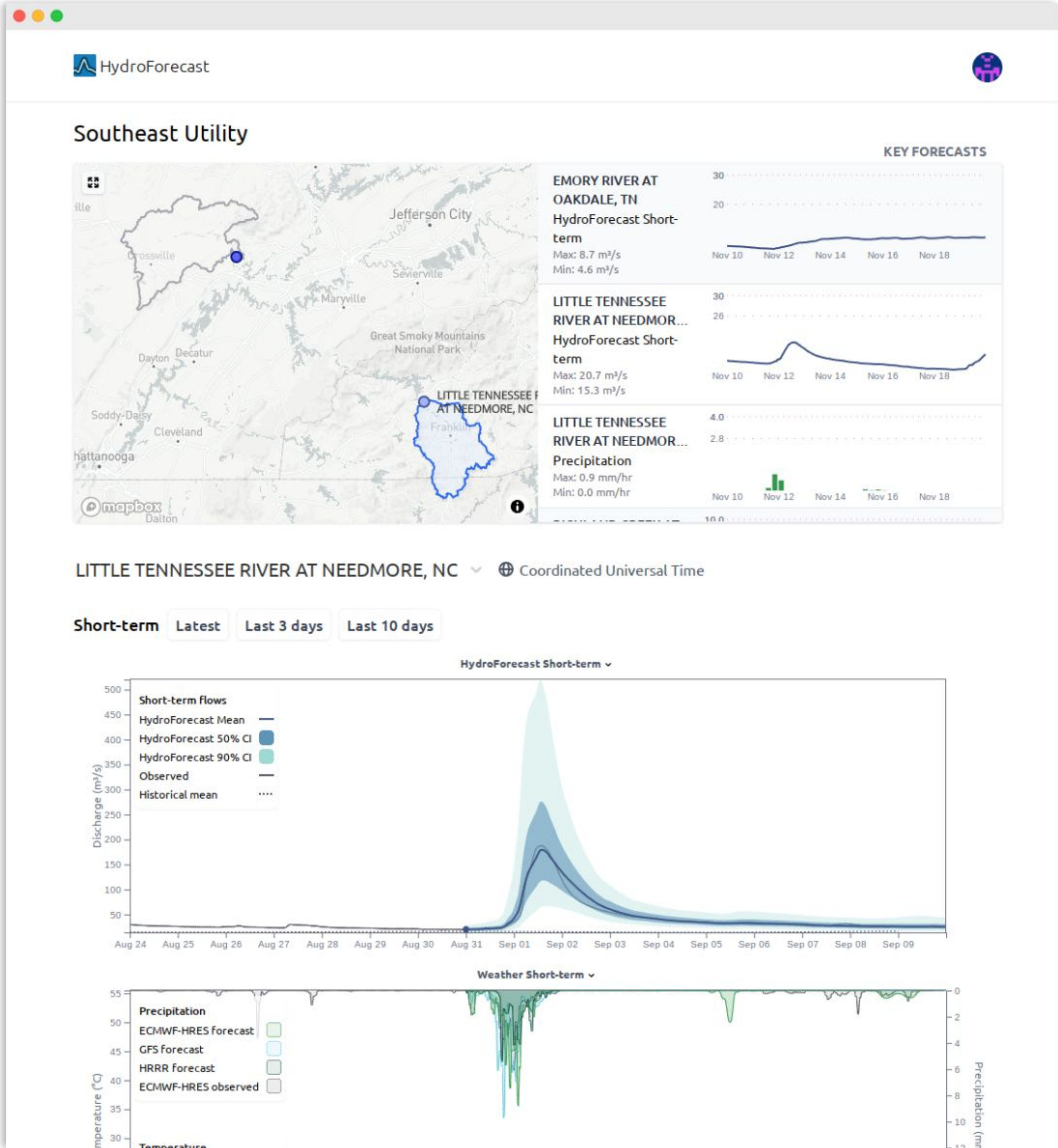
UPSTREAM TECH

We build software to accelerate the pace and scale of environmental and climate work across the globe.

Our team: software and machine learning, water resource management, and environmental science.

HydroForecast

- 10 day and seasonal flow forecasts + Ungauged reanalyses
- Theory-guided machine learning modeling approach
- Hydropower, environmental, water supply users



Today

- The streamflow forecast rodeo
- Patterns in the results
- What led to our success

The Streamflow Forecast Rodeo

- Organized by CEATI and USBR
- Sponsored by DOE, USBR, TVA, Southern Co and Hydro-Québec
- 1 year, 19 sites
- Daily streamflow forecasts, 1-10 day horizon, 6 hour step
- Any approach, any input
- 3rd party verified by RTI
  - NSE, RMSE, Correlation, Bias

- Forecasters: Utilities, NOAA RFCs & NWM, companies, research labs, and individuals

Category Winners

	Winner by Region (Sponsor)				
Category	**U.S. West** USBR	**U.S. Southeast** TVA	**Alabama** Southern Co.	**Québec** Hydro-Québec	**U.S. Mtn. West** DOE
All Arounder Leader across all metrics, horizons, seasons and flow ranges					
Flood forecaster Leader in highest flow range					NOAA
Quick draw Leader at shortest forecast horizon					
Eagle eye Leader at longest forecast horizon					
Straight shooter Leader with lowest bias		TVA			

Legend: Upstream Tech - HydroForecast TVA Tennessee Valley Authority NOAA NWS River Forecast Centers

www.linkedin.com/pulse/competition-emerging-inflow-forecasting-technologies-

USBR Public Forecast Competition

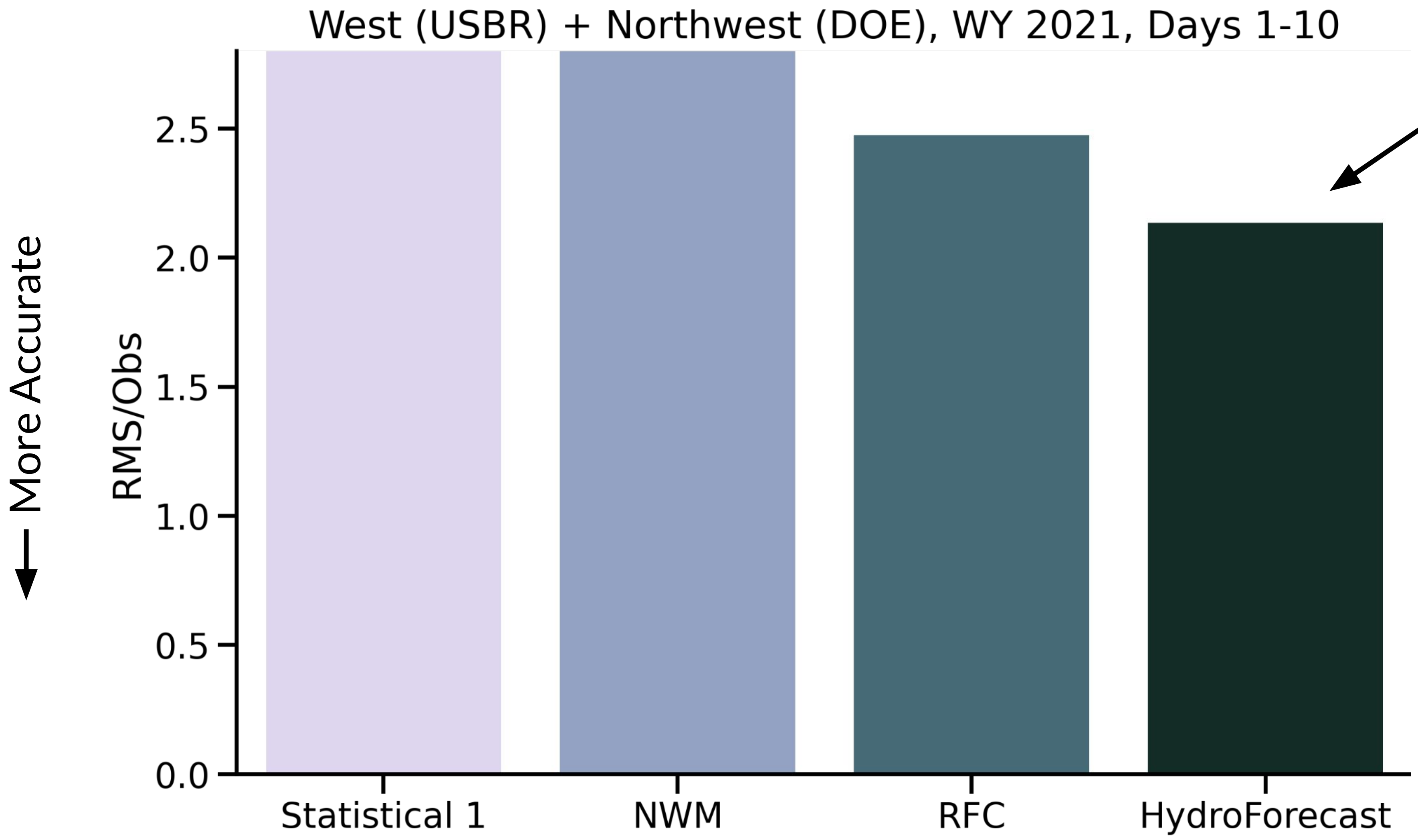
www.topcoder.com/community/streamflow

LEADERBOARDS

OVERALL | QUARTERLY | MONTHLY | HINDCAST CHALLENGE

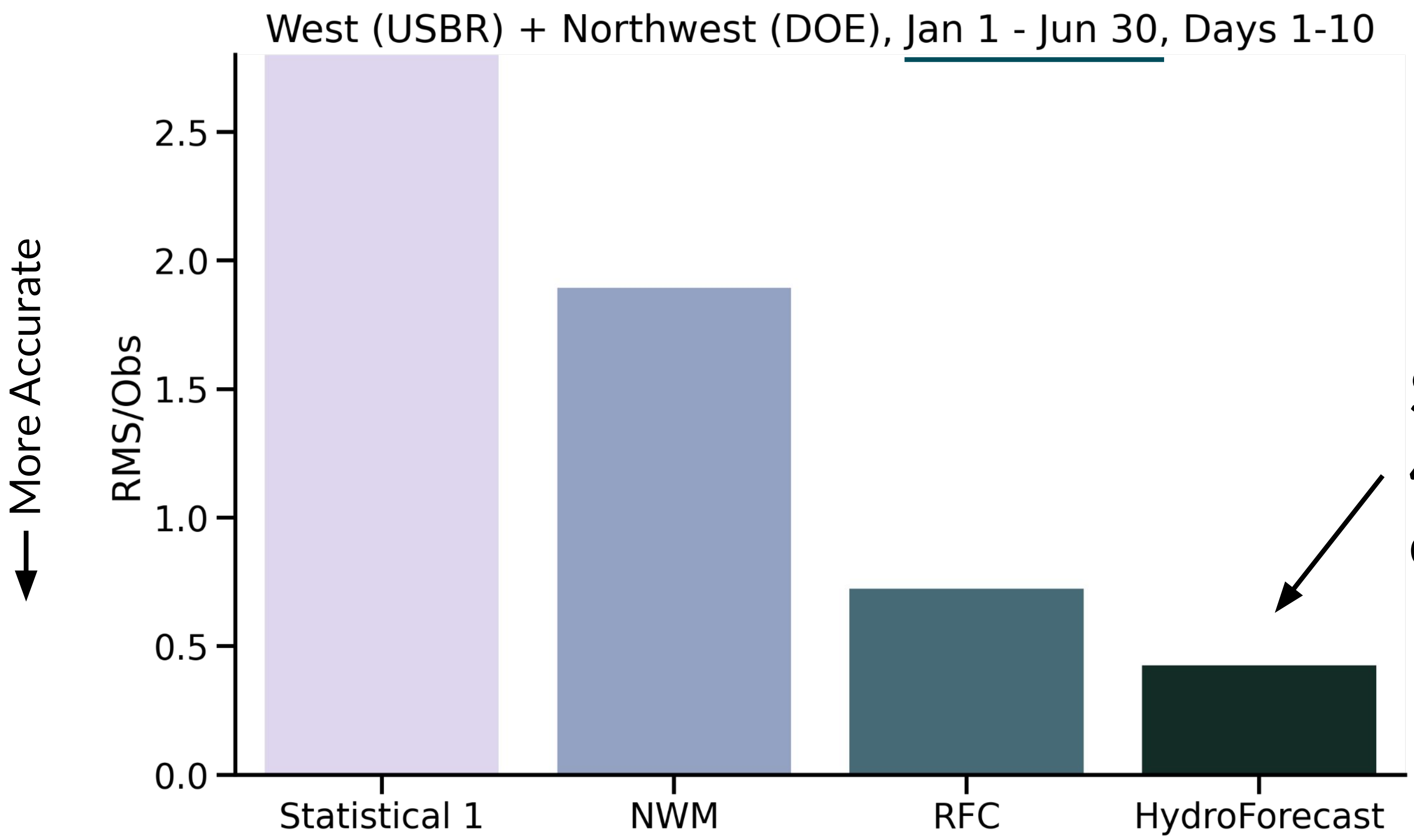
RANK	HANDLE	FINAL SCORES
1	HydroForecast (MarathonTester5)	42.46434399
2	rasyidridha	41.06575636
3	rekcahd	41.05503682
4	pfr	40.90536002
5	tcghanareddy	39.87873198
6	AliGebily	38.86461489
7	dsvolkov	38.558082
8	salmiaki	38.53459806
9	gardn999	38.02438682
10	TheRealRoman	36.94327693

Snow Driven: US West



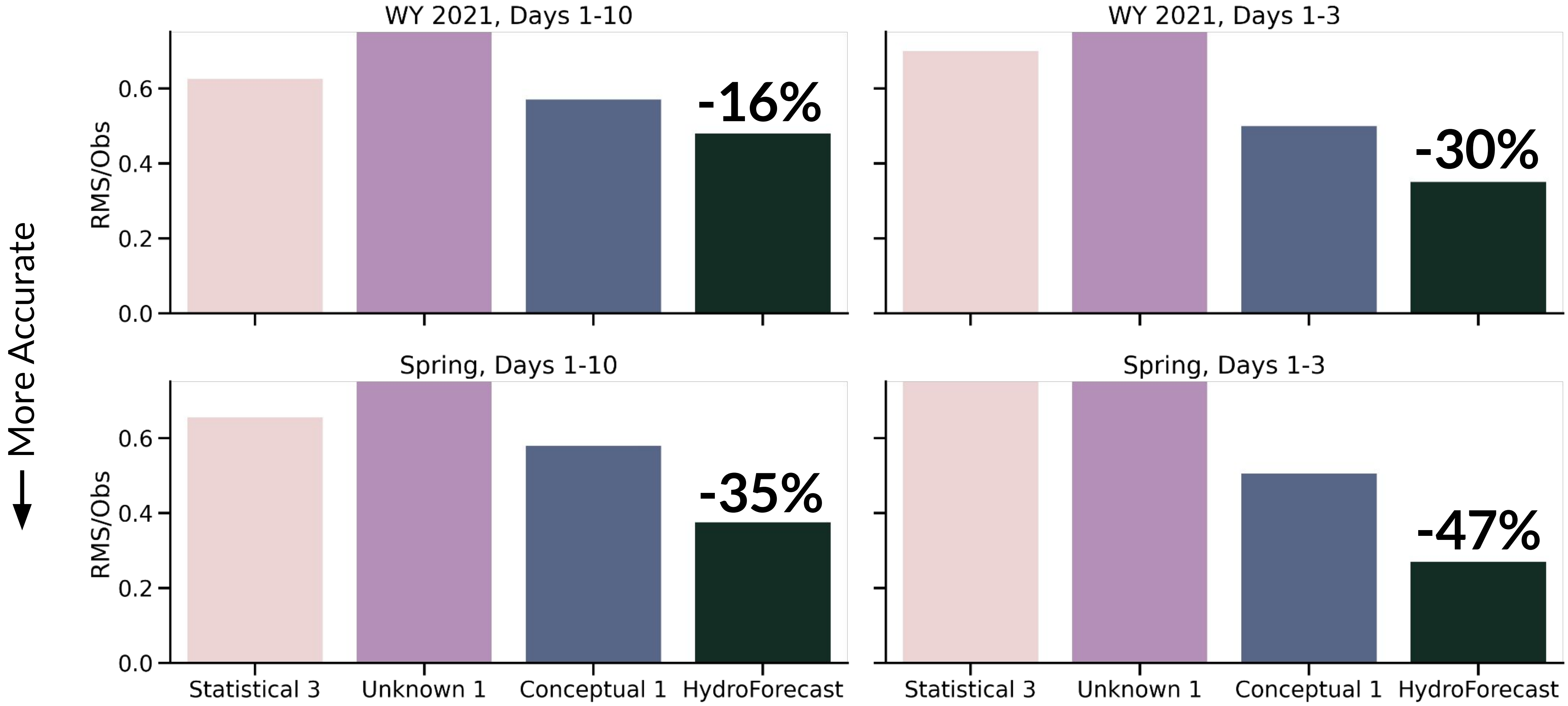
Full Year:
14% reduction in error over RFC

Snow Driven: US West



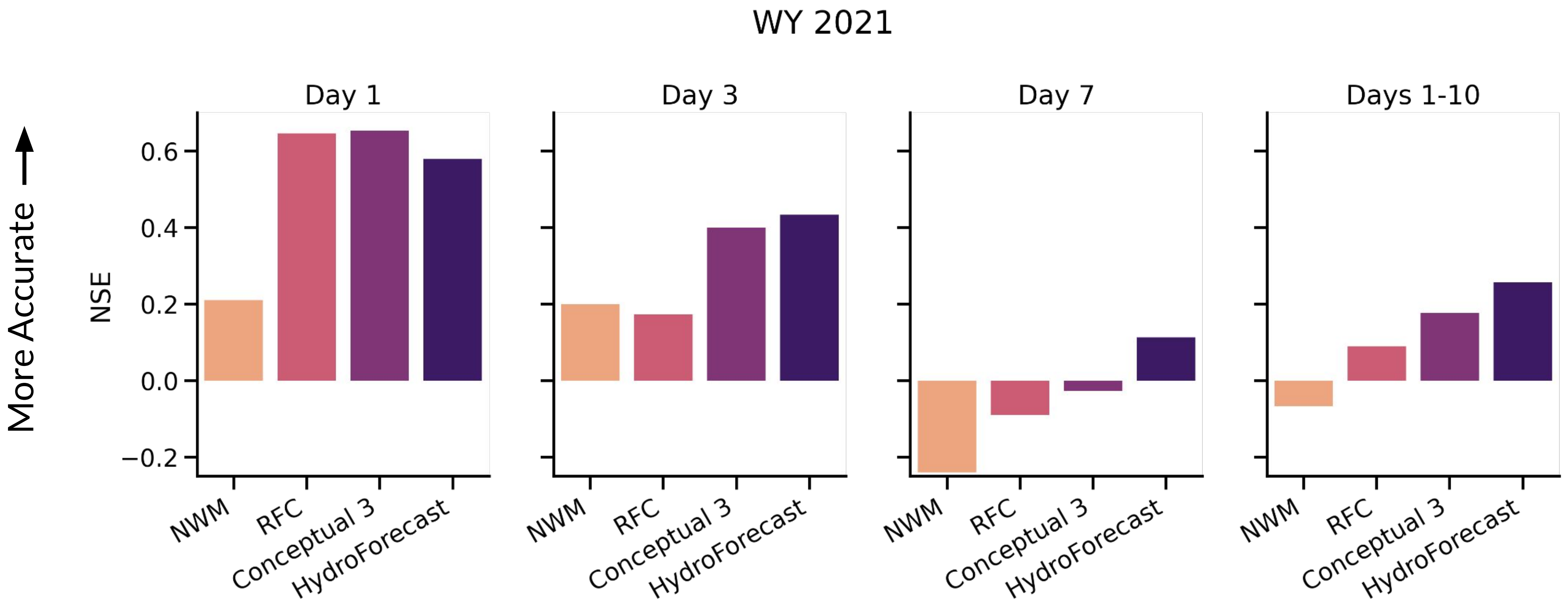
Snow melt:
41% reduction in error over RFC

Snow Driven: Québec Region



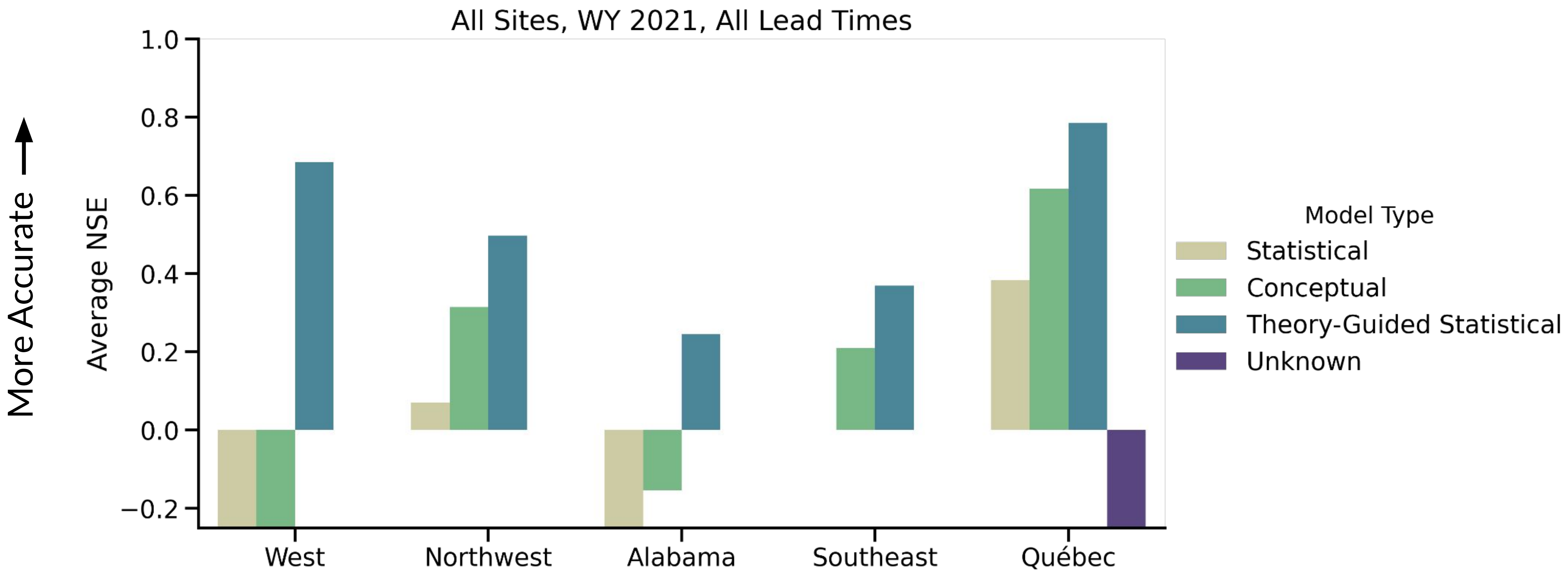
16% to 47% reduction in forecast error vs 2nd most accurate

Rain Driven: Southeast US Region



HydroForecast was only entrant with NSE > 0 one week ahead

Model Types



Very wide variation in statistical model performance

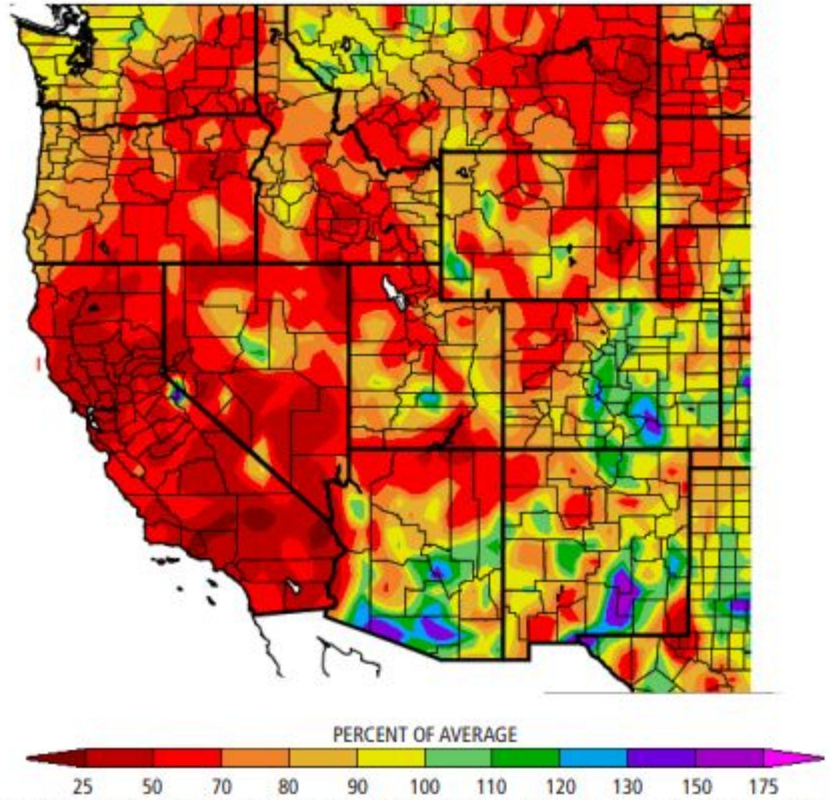
Extreme Conditions

CA Department of Water Resources, *California Water Year 2020*

“Water Year 2021 was California’s second driest year based on statewide precipitation. (Water Year 1924 was California’s driest year.)”

Strong performance in year that was drier than any our model had seen.

WY 2021 Precipitation



Generated 9/16/2021 at Western Regional Climate Center (WRCC) using provisional data.
Figure credit: Western Regional Climate Center

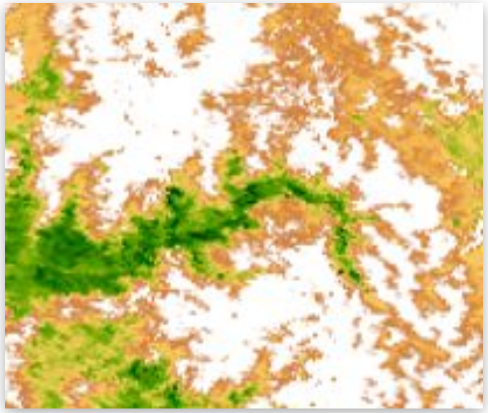
What drives our skill?

Theory-guided machine learning provides the foundation

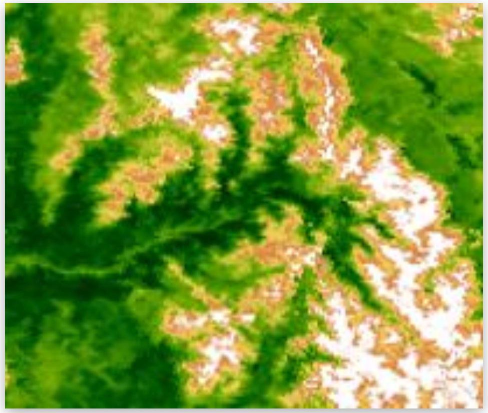
This allowed us to leverage

- Large, diverse training datasets
- Multiple weather forecasts
- Satellite observations
- Automatic gauge data assimilation

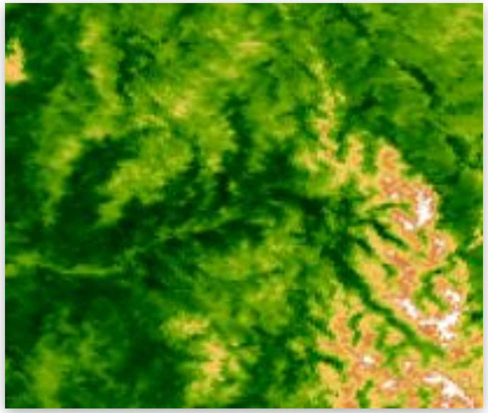
Satellite Vegetation & Snow



April 23



May 25

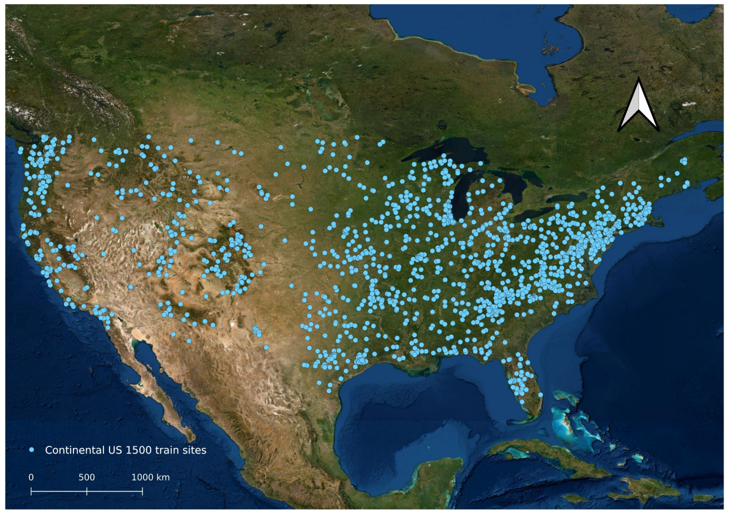


June 26

Two Phase Training

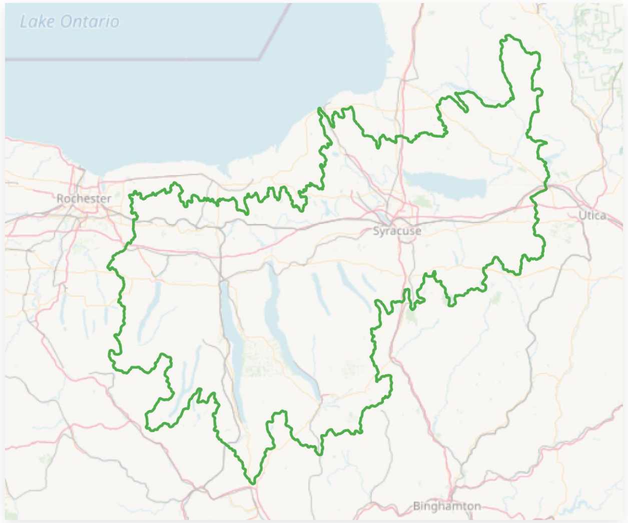
Phase 1 - Base Model

- Learn general hydrologic relationships
- Dataset contains 100s of basins



Phase 2 - Tuned Model

- Learn hydrology of specific drainage
- Dataset contains one (or a few) basins

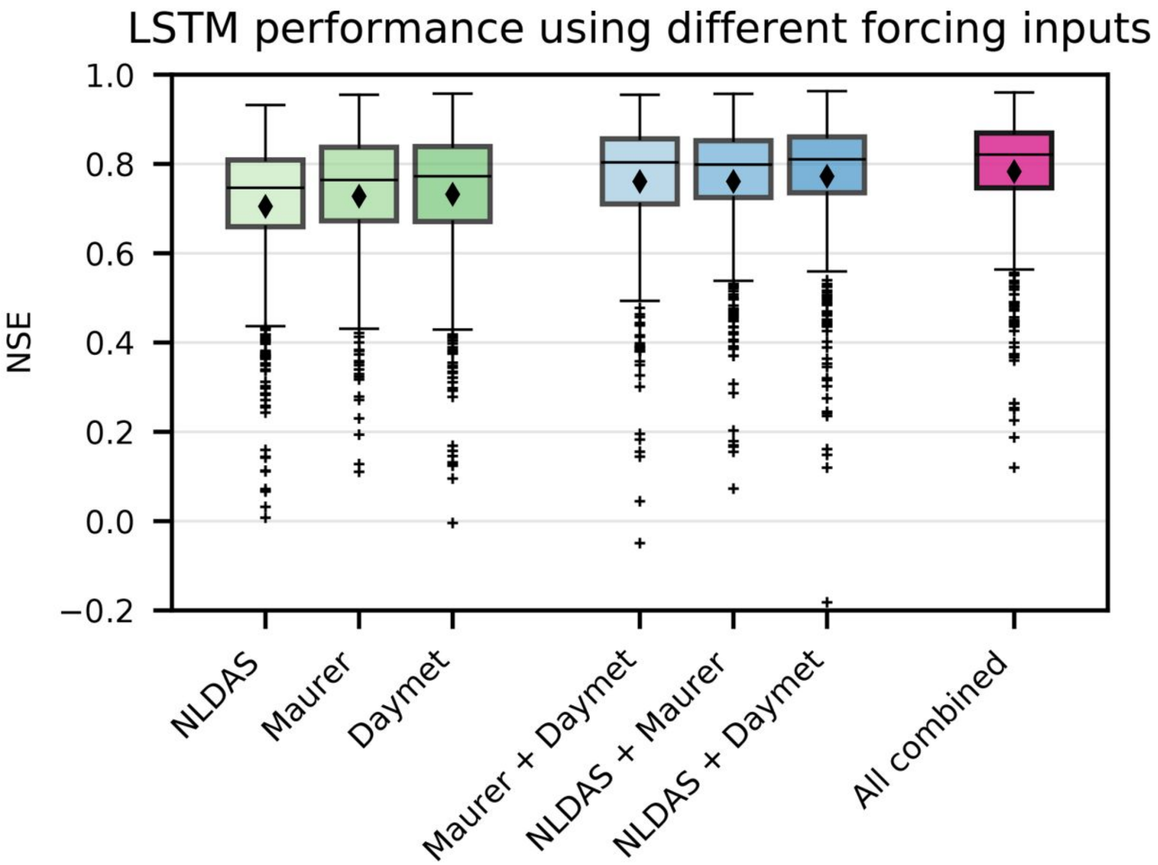


Multiple Weather Forecasts

All weather forecasts are wrong.

Let the model see multiple forecasts at once and learn to use the mutual information between them.

In the competition we used GFS and ECMWF-HRES. Added more since.



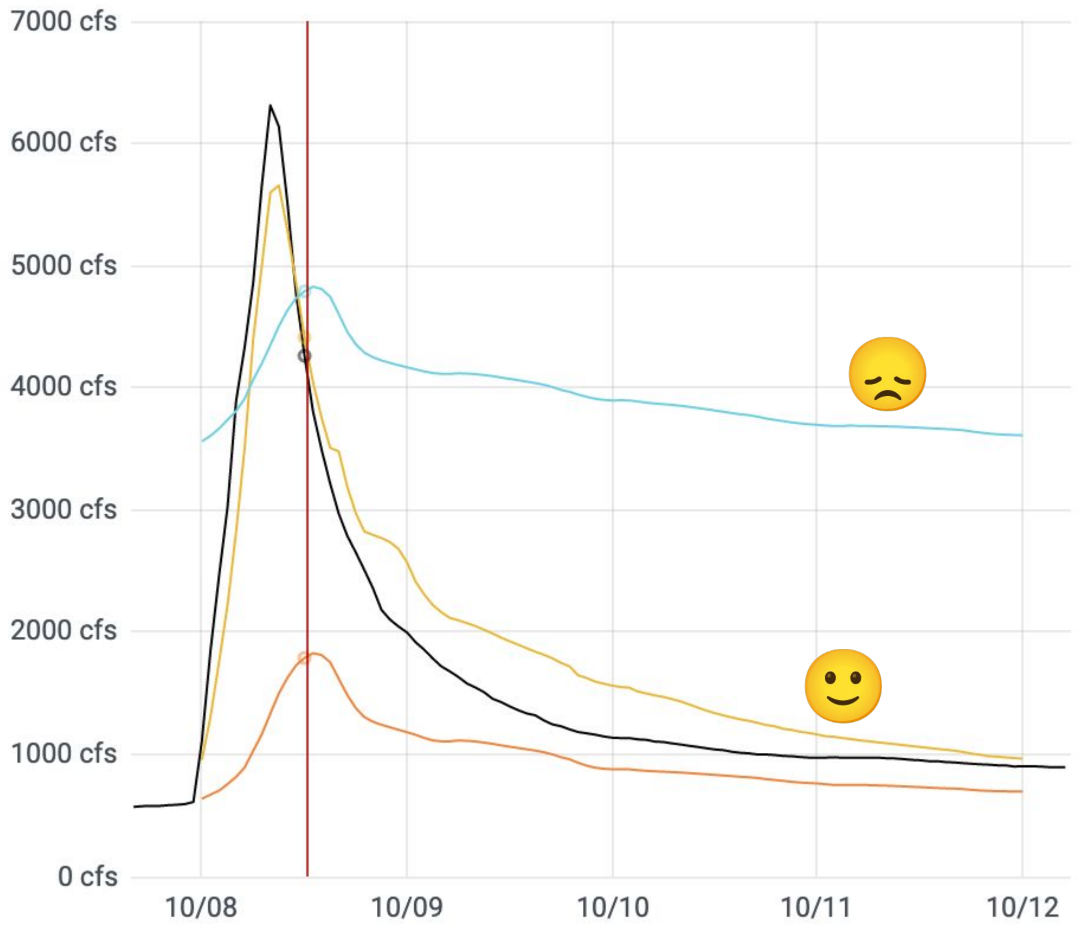
Kratzert, F., Klotz, D., Hochreiter, S., and Nearing, G. S.: **A note on leveraging synergy in multiple meteorological data sets with deep learning for rainfall–runoff modeling**, Hydrol. Earth Syst. Sci., 25, 2685–2703, https://doi.org/10.5194/hess-25-2685-2021, 2021.

Flow Observation Assimilation

Goal: use recent streamflow observations to improve forecast

Possible approaches

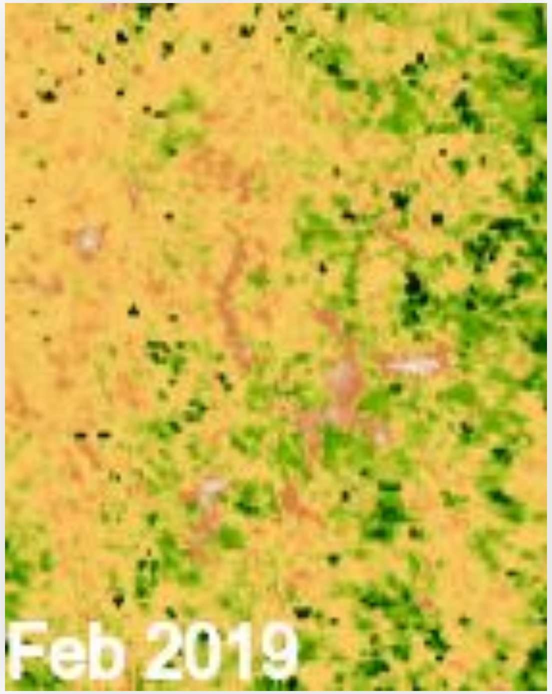
- Bias shift (with decay)
- Add observations as input (autoregressive model)
- Update states to better represent true state of the system



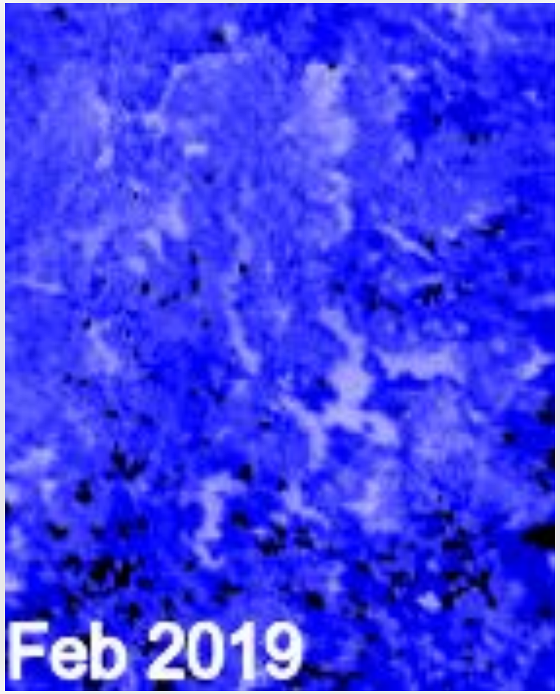
Nearing, G. S., Klotz, D., Sampson, A. K., Kratzert, F., Gauch, M., Frame, J. M., Shalev, G., and Nevo, S.: **Technical Note: Data assimilation and autoregression for using near-real-time streamflow observations in long short-term memory networks**, Hydrol. Earth Syst. Sci. Discuss. [preprint], https://doi.org/10.5194/hess-2021-515, in review, 2022.

Satellite Observations

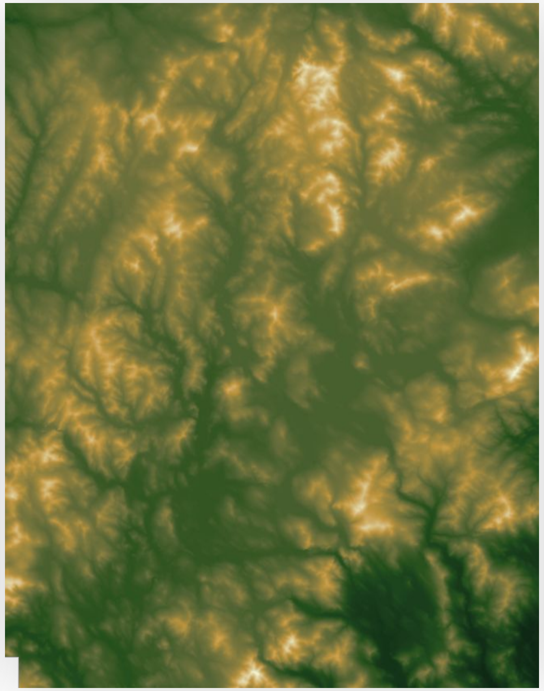
Vegetation



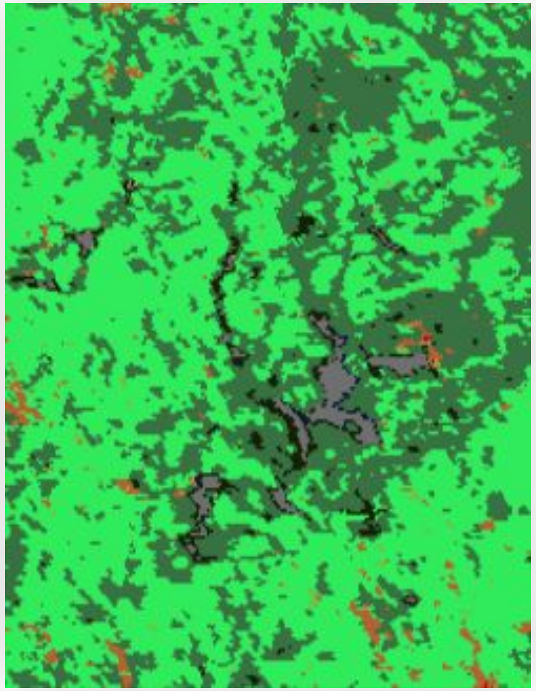
Snow



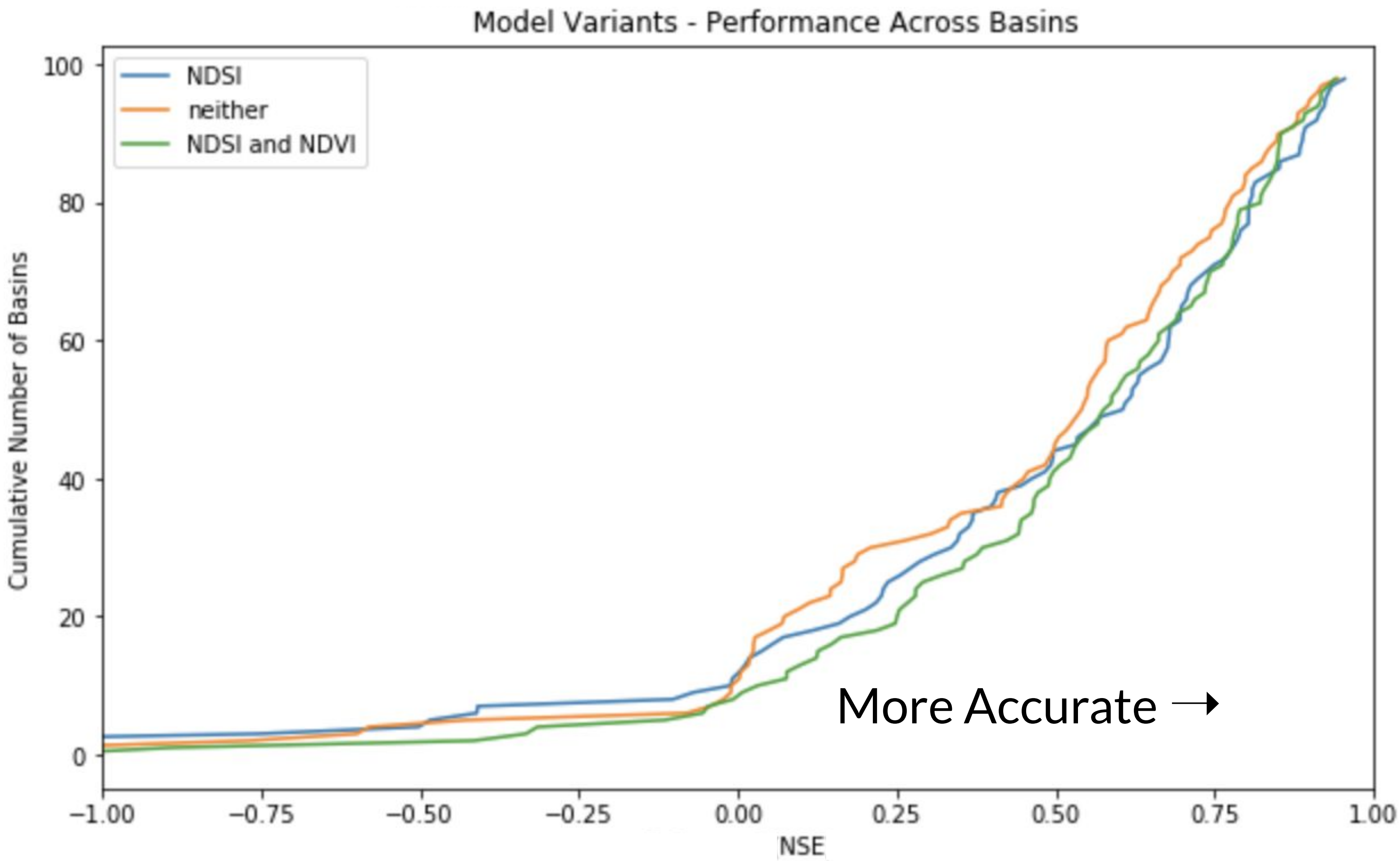
Elevation



Land cover



Satellite Observations

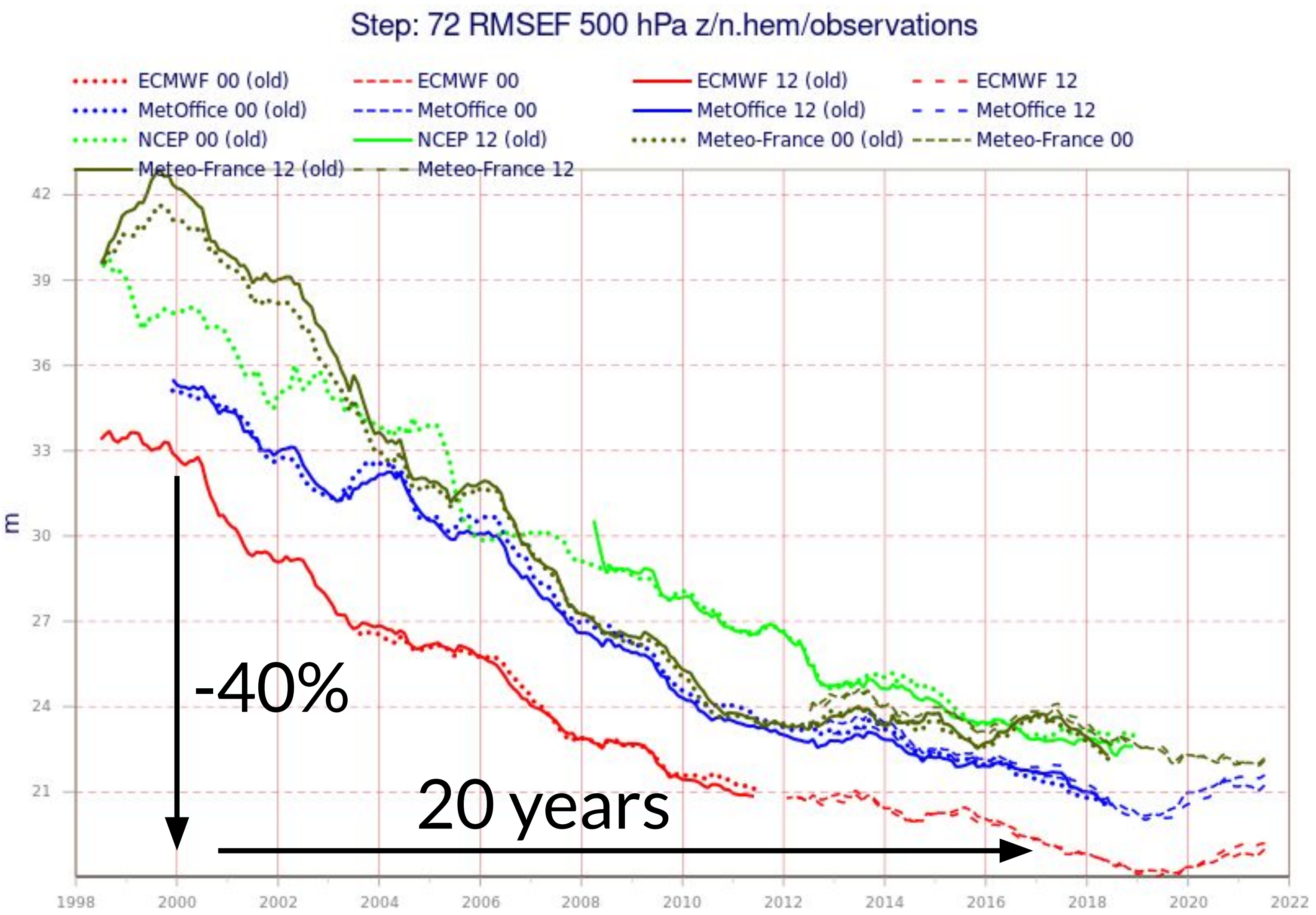


Helps most in worst performing basins

Takeaways

- Lots of room for improvement
- ML models outperformed under novel, very dry conditions
- Conceptual models broadly did not perform as well
  - Gap between ML and conceptual was smallest at flashy, rain driven sites
- Large variation in statistical model performance
  - How machine learning methods are applied matters
- Strongest performance came from theory-guided ML
  - Layered suite of techniques

Forecast Improvement in Context



https://apps.ecmwf.int/wmolcdnv/scores/time_series/500_z

The world's best weather forecasts improved by about 40% in 20 years

Thank you!

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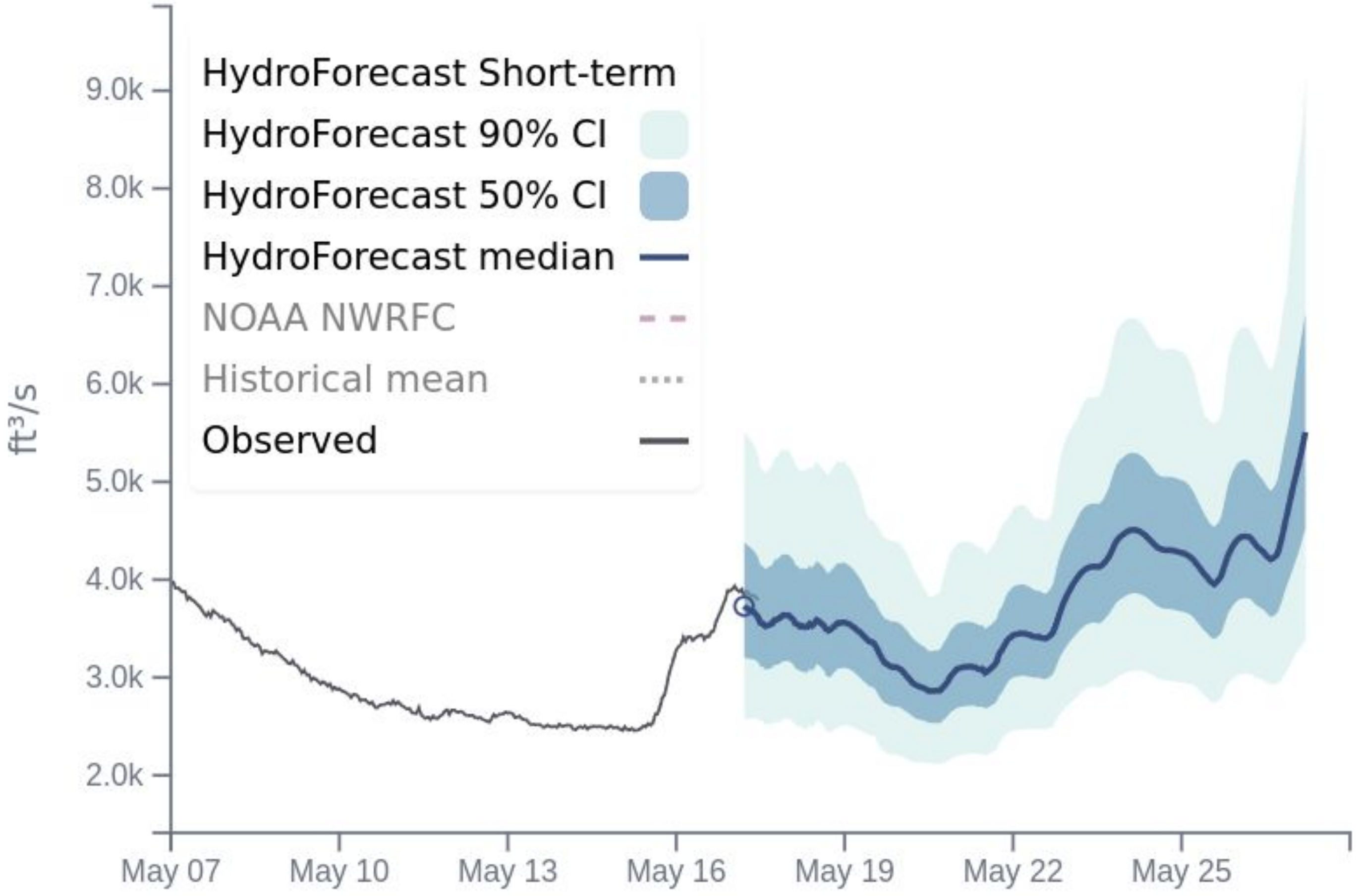
USGS Big Thompson at Estes Park, CO site visit

Appendix

Probabilistic Forecasts

Model learns to predict forecast certainty based on:

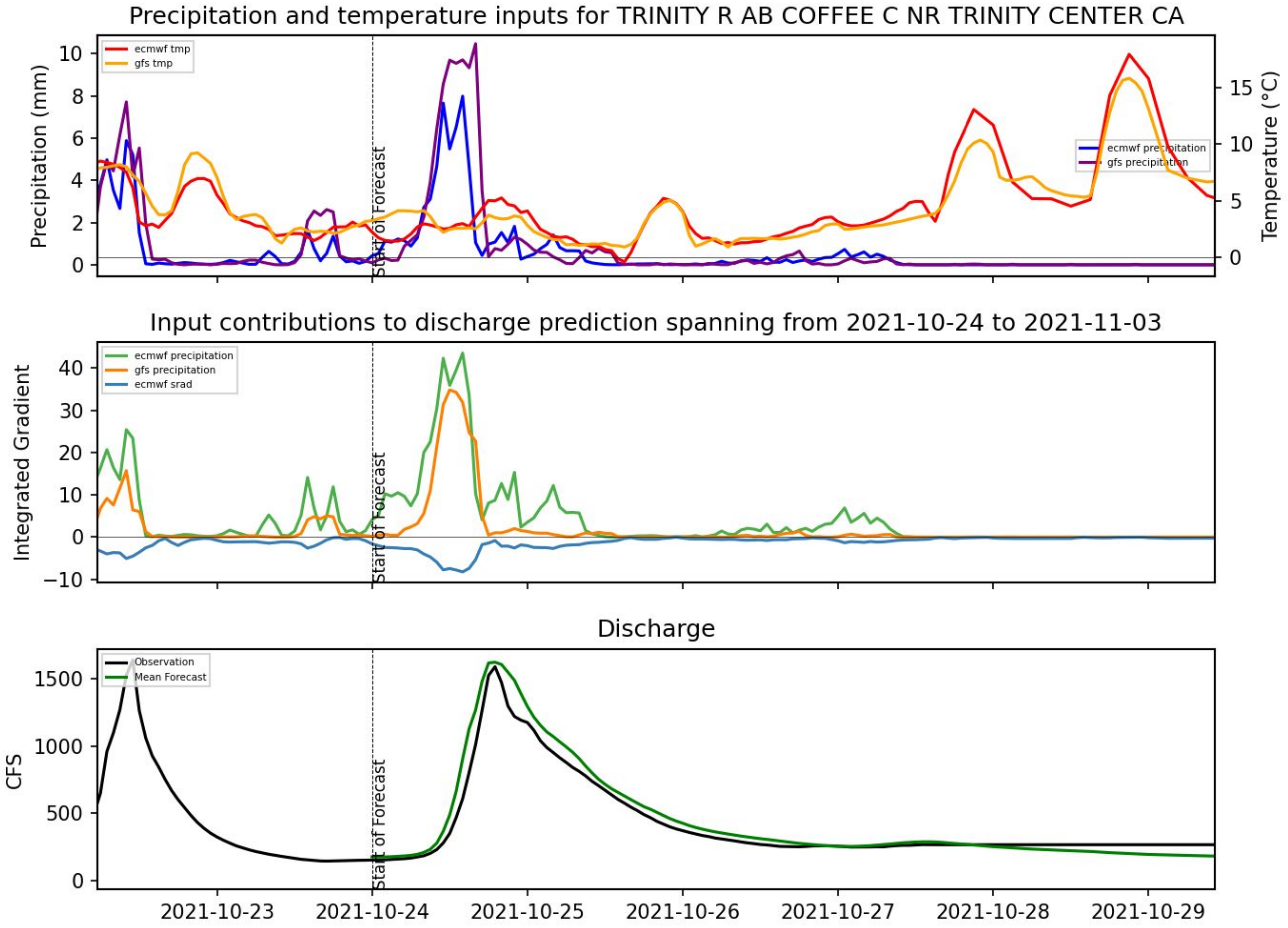
- (Dis)agreement between weather forecasts
- Basin hydrologic state
- Forecasted conditions (eg. rain on snow)
- Observation & model uncertainty



Model Inspection

Relationship between inputs and outputs

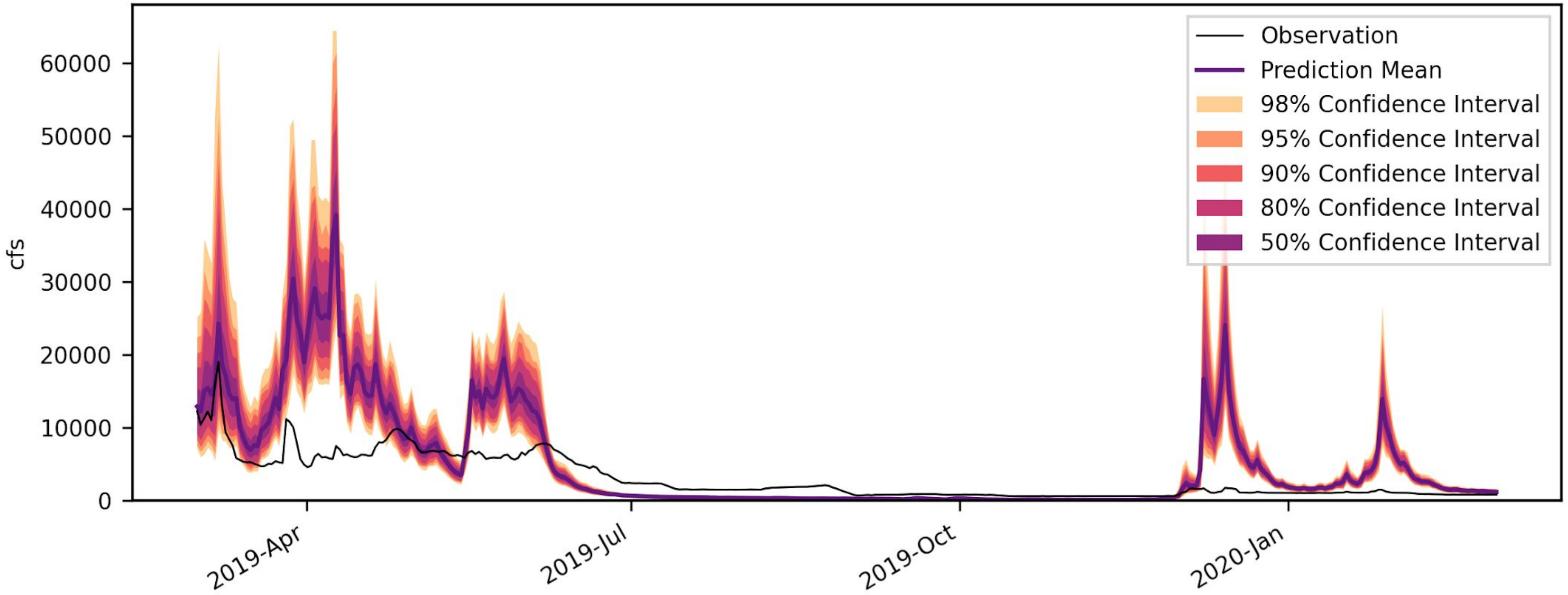
Technique: Integrated gradients (Sundararajan et al. 2017)



Human Altered Flow Prediction

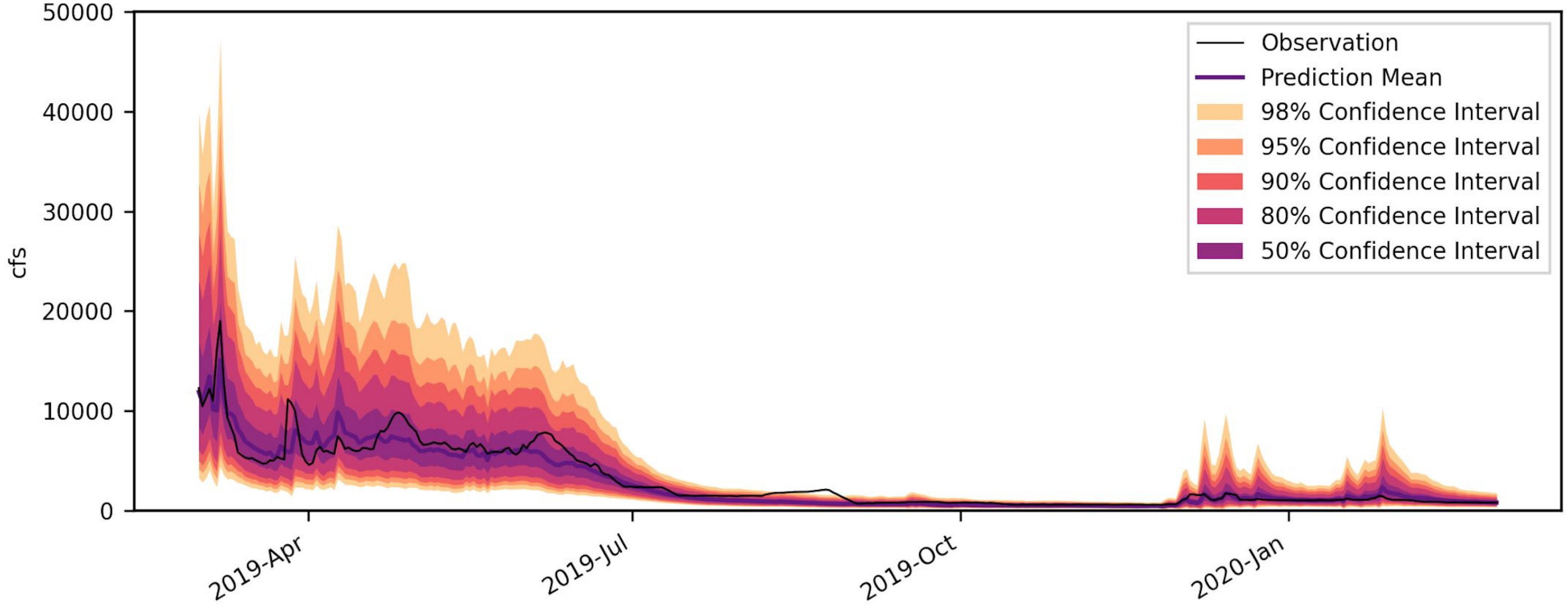
Unimpaired Model

No human impact inputs



Actual Flow Model

Includes inputs describing dams, agriculture, development, etc.



Ungauged Predictions

Across 531 basins in the US

- *Ungauged* neural network, NSE **0.69** (Early 2019 version)
- *Gauged* SAC-SMA, NSE **0.64**

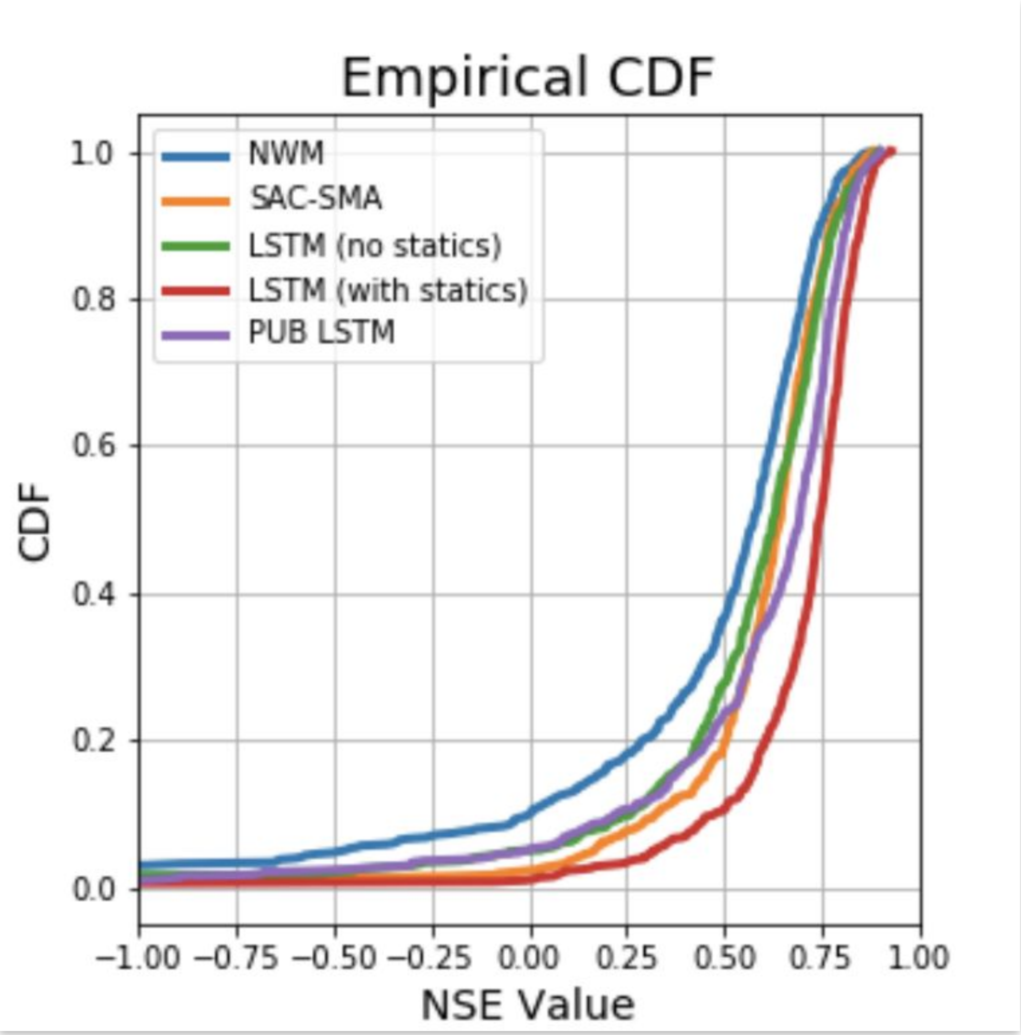
Water Resources Research

Technical Reports: Methods

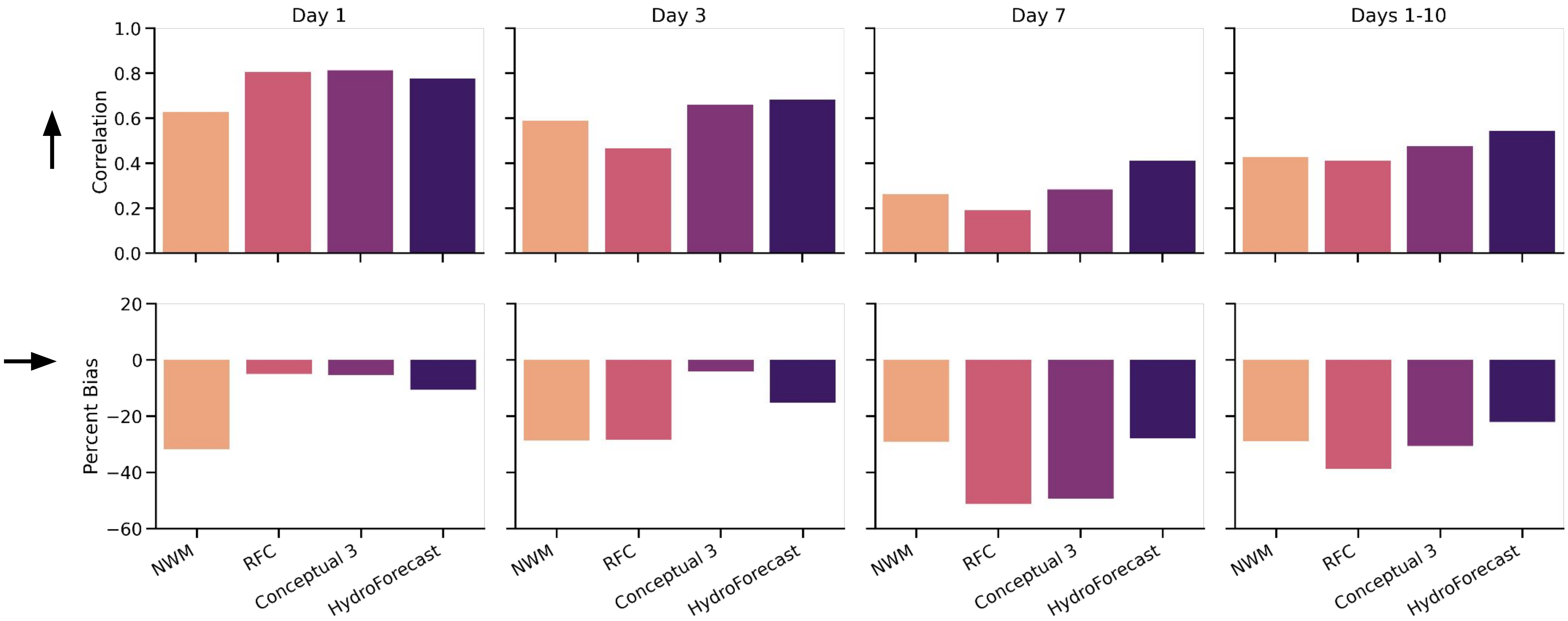
Towards Improved Predictions in Ungauged Basins: Exploiting the Power of Machine Learning

Frederik Kratzert, Daniel Klotz, Mathew Herrnegger, Alden K. Sampson, Sepp Hochreiter, Grey S. Nearing

First published: 23 November 2019 | https://doi.org/10.1029/2019WR026065



Rain Driven: Southeast US Region



Decent correlation: we know when flows will rise
Biased low: volume is less certain